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AGRONOMY AND SOILS

Using Precipitation Forecasts to Irrigate Cotton

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ABSTRACT

In this experiment, precipitation forecasts were used to schedule irrigation for cotton (*Gossypium hirsutum* L.). Four irrigation treatments and two cotton varieties were evaluated at Stripling Irrigation Research Park located near Camilla, GA in 2014. Two treatments were irrigated based on forecasts from the European Centre for Medium-Range Weather Forecasts (ECMWF) Ensemble Prediction System (EPS) and The Weather Channel®'s mobile app. Irrigation amounts for these two treatments were determined by the Cotton Irrigation Schedule Suggested for High Yields (check-book recommendations). The third treatment was irrigated by the check-book method and the fourth was rainfed. Irrigation applied for each treatment was 34.8 cm, 26.7cm, and 31.9 cm for the ECMWF EPS, weather.com, and check-book, respectively. Rainfed cotton received 16.56 cm in precipitation. All irrigation methods resulted in significantly higher yields than the rainfed cotton. Results suggest using precipitation forecasts to schedule irrigation could provide a convenient alternative to the check-book method.

Recent droughts throughout the country and the continuing water disputes among the states of Georgia, Alabama, and Florida have made agricultural producers more aware of the importance of managing irrigation systems efficiently. Some southeastern states are beginning to consider laws that will require monitoring and regulation of water used for irrigation. In fact, Georgia recently suspended issuing irrigation permits in some areas to try and limit the amount of water used in irrigation (Hollis, 2013).

Even in southwest Georgia, which receives on average 59.06 cm (23.25 in) of rain during the growing season, irrigation can significantly impact crop yields. Studies have shown there can be large differences between dry-land cotton (*Gossypium hirsutum* L.) production and irrigated yield. For example, Farahani and Munk, 2012 pointed out that if sufficient rainfall fails to occur at critical times during the growth cycle of cotton (during the reproductive stages, from floral budding to peak bloom), yield can be less than half that of irrigated fields.

Many different irrigation scheduling tools are available for producers, some of which include the input of current weather data from nearby stations (Leib et al., 2012). Most published literature concentrating on weather occurring during the growing season emphasizes the role of large-scale patterns on crop production (Baigorria et al., 2008; Hansen et al., 1998, 2001; Paz et al., 2012) and does not investigate the effects of using short-term weather forecasts for management decisions.

Check-book method. In this study, using precipitation forecasts to schedule irrigation is compared to an accepted irrigation practice referred to as the check-book method. The check-book method is a straightforward scheduling aid (University of Georgia Cooperative Extension/ College of Agricultural and Environmental Sciences, 2014). This method has proven to be a simple and effective way to promote high yields.

To follow the method, producers keep a record of observed rainfall and subtract the observed amount from the total amount of irrigation recommended by the Cotton Irrigation Schedule Suggested for High Yields (University of Georgia Cooperative Extension/ College of Agricultural and Environmental Sciences, 2014) provided in Table 1. However, there are caveats to the rule. If an intense, quick rainfall occurs on the field in which runoff is assessed qualitatively by the producer as being high, then the total amount of rainfall in that event may not be subtracted from the recommended amount of irrigation for the time period. Also, if rainfall occurs in the midst of several hot, dry days, then the event would not be subtracted from the recommended amount, if the producer observes the ground to be relatively dry at the time of planned irrigation. During experimentation, the Check-book Treatment was irrigated according to this method.

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Table 1. Cotton Irrigation Schedule Suggested for High Yields and Twice Per Week Application Rates (University of Georgia Cooperative Extension/ College of Agricultural and Environmental Sciences, 2014)

Crop Stage	mm/week	mm/application
Week beginning at 1st bloom	25.4	12.7
2nd week after 1st bloom	38.1	19.0
3rd week after 1st bloom	50.8	25.4
4th week after 1st bloom	50.8	25.4
5th week after 1st bloom	38.1	19.0
6th week after 1st bloom	38.1	19.0
7th week to 1st open boll	25.4	12.7

European Centre for Medium-Range Weather Forecasts (ECMWF) Ensemble Prediction System (EPS) probabilistic precipitation forecasts. The ECMWF EPS generates probabilistic precipitation forecasts. These forecasts were adjusted and used to irrigate the Bias-Adjusted ECMWF EPS Treatment (see Materials and Methods.) The ECMWF EPS consists of a global atmospheric general circulation model, a data assimilation system, a land surface model, an ocean wave model, and an ensemble forecasting system. The horizontal resolution of the model is 0.25° (approximately 27 km) (Persson, 2011). The model divides the vertical component of the atmosphere into 91 layers covering 64 km at up to 0.1 hPa resolution in the planetary boundary layer, decreasing upward into the stratosphere and lower mesosphere (British Atmospheric Data Centre, 2015).

In contrast to deterministic forecasts, which provide one model result per grid point, the ECMWF EPS produces multiple model outcomes per grid point that are intended to compensate more adequately for initial analysis and model error. Forecasts such as these are designed to provide a measure of the forecast uncertainty and probability from which alternative scenarios and strategies can be developed. The ECMWF EPS generates a total of 51 forecasts (ensemble members) for each time step, consisting of the control forecast (the unperturbed model run, which is also run at a finer resolution) in addition to 50 forecasts produced from perturbed model states. These perturbed forecasts are used to represent initial analysis error (by perturbing the initial analysis) and model error (by using stochastic processes to represent errors in model physics). The probability of occurrence of an event (i.e., rainfall above or below some threshold) can be characterized by the number of ensemble members predicting the event divided by the total number of members (Persson, 2011).

Weather.com forecasts. The Weather Channel®'s mobile app (http://www.weather.com/apps) was chosen as the second forecast option due to its accessibility and popularity. Due to its close proximity to Stripling Irrigation Research Park (SIRP), Camilla, GA was set as the forecast location in the app. Unlike the ECMWF EPS, probabilities for precipitation issued by weather.com were not determined based upon a set threshold for an amount of precipitation, but rather upon the probability of receiving any measurable rainfall (considered to be greater than 0.254 mm [0.01 in]).

Although using seasonal weather forecasts for agricultural decision making (e.g., crop and variety decisions) is promising (Crane et al., 2010), the use of more reliable short-term forecasts might have substantial benefits for producers as well. The objective of this experiment was to explore the potential of using precipitation forecasts to schedule irrigation. This is shown by comparing yield, irrigation water use, and forecast performance among the treatments.

MATERIALS AND METHODS

Experimental design. Two cotton varieties, PhytoGen® 499 WRF ('PHY 499 WRF', considered to be more drought tolerant) and FiberMax® 1944 GLB2 ('FM 1944 GLB2', considered to be more responsive to water), were planted in a split block design at the University of Georgia's (UGA) SIRP located near Camilla, GA (31° 16′ 48.288" N, -84° 13′ 10.5594" W, 49 m elevation above sea level). The experiment consisted of four irrigation treatments: Rainfed, Check-book, Weather.com, and Bias-Adjusted ECMWF. Other than differences in irrigation, management practices used throughout the season were consistent across treatments.

Each treatment was replicated three times, with each sub-block consisting of two varieties subjected to one of the four irrigation treatments. Rows were 91 cm (36 in) wide and 13.7 m (45 ft) long. Seeds were sown at 3 seeds/30.5 cm (3 seeds/ft) with a Monosem® (Edwardsville, KS) vacuum planter on 7 May 2014 in Lucy loamy sand, characterized as being very deep, well drained, and moderately permeable. Irrigation was initiated with squaring, which began the week of 8 June 2014 and ceased upon boll opening, which began 30 August 2014. A 3-Span Valley® (Valley, NE) Linear Endfeed 8000 with Nelson® (Walla Walla, WA) S3000 Spinner sprinklers regulated at low pressure was used to apply irrigation. The drop hose was held constantly at approximately 2.03 m (80 in) from the ground to the base of the sprinkler. A two-row 9930 John Deere® spindle harvester with bagging attachments was used to harvest the crop on 6 October 2014. Seed cotton was ginned through the UGA Microgin.

For the Rainfed Treatment, cotton only received water during the limited number of rainfall events that occurred throughout the 2014 growing season. For the other three treatments, irrigation schedules and amounts were based upon values derived from the Cotton Irrigation Schedule Suggested for High Yields (CISSHY) found in Table 1 (University of Georgia Cooperative Extension/ College of Agricultural and Environmental Sciences, 2014). This table recommends irrigation based upon cotton crop stage and commonly is followed when applying the check-book method of irrigation.

Irrigation was scheduled twice per week on Mondays or Tuesdays for the first application and Thursdays or Fridays for the second, depending upon time and availability at SIRP. Irrigation was applied to all treatments the same day. Irrigation decisions pertaining to the Bias-Adjusted ECMWF Treatment and the Weather.com Treatment were made twice per week on Sunday and Wednesday evenings after observing the forecasts. Irrigation decisions for the Check-book Treatment were made twice per week, the evening before scheduled irrigation. However, if rainfall occurred overnight, adjustments were made the morning of irrigation. During the experiment, 1.27 cm (0.5 in) of water was not applied as prescribed to the two forecast treatments and should be noted as experimental error. The errors occurred during the same irrigation applications for both treatments.

Forecasts are available from the ECMWF EPS twice daily at 0Z and 12Z (8 pm and 8 am EDT). However, many producers are constrained by pivot size and speed to make irrigation decisions only two to three times per week. During this experiment, forecasts using the ECMWF EPS model data were issued twice per week, on Sunday and Wednesday evenings at 1700 (5 pm) EDT and communicated by e-mail. The Sunday evening forecasts included precipitation forecast data from the Sunday 0Z (8 pm EDT Saturday) ECMWF EPS model run, whereas the Wednesday evening forecasts included precipitation forecast data from the Wednesday 0Z (8 pm EDT Tuesday) model run. Forecasts from weather.com were downloaded twice per week on Sunday and Wednesday evenings at 1700 (5 pm) EDT.

Bias adjustments. Numerical Weather Prediction (NWP) models frequently display bias with respect to forecasts (Danforth et al., 2007). In an effort to reduce bias in the ECMWF EPS model forecasts, a statistical technique known as quantile-to-quantile (q-to-q) mapping (Hopson and Webster, 2010, Shrestha et al., 2014, Webster et al., 2011) was applied. For this experiment, q-to-q mapping was performed on each ensemble member to generate a corrected ensemble member forecast. As applied here, the q-to-q technique requires the creation of two cumulative distribution functions (cdfs). One cdf consists of past forecast data the other of past observations for the forecast location (or area) in question. ECMWF model hindcasts (reforecasts for previous years generated once per week using the current version of the model) were used to represent past model forecasts, and observations from the Georgia Automated Environmental Monitoring Network (GAEMN, www.georgiaweather.net) were used to represent past observations. (The process of developing the hindcast and observation cdfs is further explained in the next section.) The q-to-q technique assigns each ensemble member forecast to a quantile on the hindcast cdf. The next step takes the assigned quantile and maps it to a new, "corrected" forecast value on the observation cdf. This bias-correction process is presented in Fig. 1.

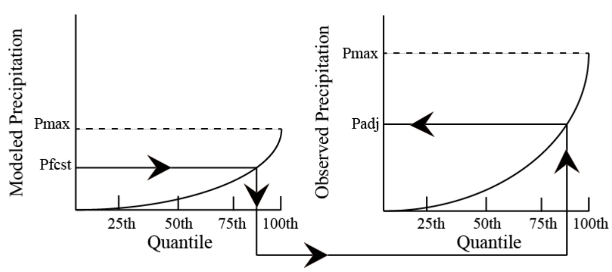

Figure 1. The q-to-q correction system. Both modeled and observed precipitation are binned into quantiles. Precipitation is represented on the y-axis. The modeled precipitation is mapped onto the observed precipitation fields by setting respective modeled quantiles to observed quantiles. In the figure, the forecast precipitation (P_{fcst}) of the 85th quantile is set to the observed precipitation (P_{adj}) of the 85th quantile. (Hopson, et al., 2010)

Hindcasts and observations. In an effort to measure model performance, the ECMWF runs the most current EPS with fewer ensemble members (5 instead of 51) using past data to initialize the run. These are referred to as hindcasts, and they are run for the entire globe once per week for that calendar day over the previous 18 yrs. For this experiment, hindcasts taken from a sampling of grid points near

GAEMN stations in the vicinity of SIRP from 1 May 2013 through 15 August 2013 were used to represent the past model forecasts in a cdf to be used in the q-to-q correction process. For each chosen station, hindcasts from the nearest five grid points were included in the cdf. Cumulative distribution functions were created for each lead day generated by the model. This made it possible to apply q-to-q corrections specifically for every forecast lead day.

Hindcasts from grid points near the following GAEMN stations were included in the model corrections: Camilla (located at SIRP), Tifton, Dawson, Cordele, Newton, Moultrie, Attapulgus and Dixie. The hindcast cdf is represented by the plot on the left-hand side of Fig. 1, with modeled precipitation represented on the y-axis. Observations taken during the time period beginning 1 May and running through mid-August over the previous 18 yrs from the above GAEMN stations were used to generate a cdf of observations. The observation cdf is represented by the plot on the right-hand side of Fig. 1, with observed precipitation represented on the y-axis. Figure 2 shows the hindcasts for lead day one plotted versus the historical observations, illustrating a tendency (bias) to under-predict precipitation for larger observed values. Therefore, the q-to-q corrections helped improve the model's tendency to under-predict precipitation by mapping it to larger values for the same quantile on the observed cdf.

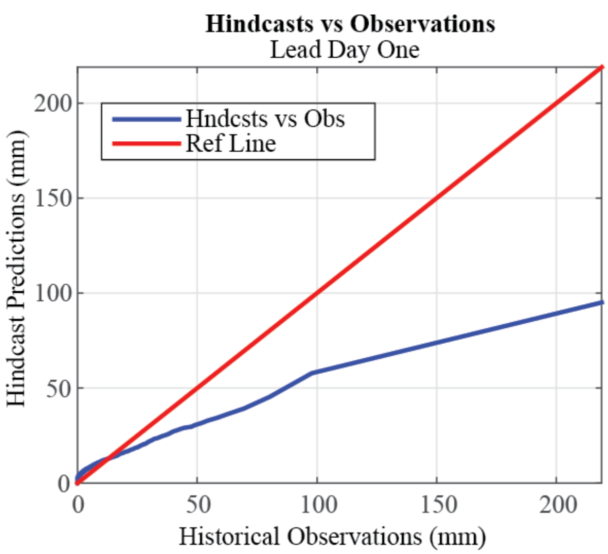

Figure 2. Lead day one plot of hindcasts versus historical observations. Hindcasts tend to over-predict precipitation in the lower values while under-predicting in the upper values.

Bias-adjusted forecasts. The above correction technique was applied to each ensemble member generated by the ECMWF EPS precipitation forecasts, creating 51 Bias-Adjusted ECMWF EPS forecasts for each chosen grid point. Grid points chosen for the forecasts included data from an approximate 1° latitude-longitude box surrounding SIRP. To summarize, there were 51 ensemble members produced at each grid point and 25 grid points chosen for analysis. The forecast probabilities issued were the percent number of ensemble members that predicted at least a threshold value of precipitation would occur as described in Eqs. 1 and 2, below. These Bias-Adjusted ECMWF EPS forecast probabilities were then communicated twice per week via e-mail. An example forecast is shown in Fig. 3.

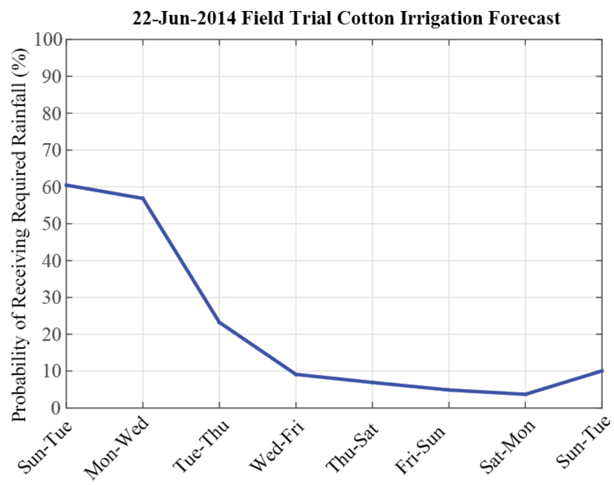

Figure 3. 22 June 2014 Bias-Adjusted ECMWF Treatment forecast.

$$Total\ No\ of\ Ens\ Members = 51 \frac{ens\ members}{grid\ point} * 25\ grid\ points = 1275\ Total\ Ens\ Members \quad (1)$$

$$Forecast\ Probability = \frac{number\ of\ ensemble\ members \geq threshold}{total\ number\ of\ ensemble\ members} \quad (2)$$

Precipitation thresholds. Precipitation thresholds were developed for the Bias-Adjusted ECMWF Treatment so that forecast probabilities could be calculated for each time period. Irrigation began upon squaring, and from the onset of irrigation through the first week of bloom, the forecast thresholds were set at 12.7 mm (0.5 in). This threshold matched the CISSHY found in the 2014 UGA Cotton Production Guide provided in Table 1. Following the first week of bloom and for the remainder of season, the forecast thresholds were set at 2.54 mm (0.1 in), 5.08 mm (0.2 in), 7.62 mm (0.3 in), and 10.2 (0.4 in) for each forecast. If the probability of receiving one of the lower precipitation thresholds exceeded the probability limit, then it was subtracted from the total amount recommended by the CISSHY.

Probability limit. A probability limit was set for the experiment so that any forecast exceeding it would trigger cancellation of the planned irrigation. This limit was set somewhat liberally at 60%

to compensate for conservative model estimates of the predominantly convective nature of precipitation occurring in Southwest Georgia during the growing season (Tiedtke, 1989). The decision to irrigate cotton included in the Bias-Adjusted ECMWF Treatment was based upon a 60% probability of exceeding the set threshold amount of precipitation occurring between Monday and Wednesday (for the Sunday-issued forecasts) and Thursday through Sunday (for the Wednesday-issued forecasts). Cotton included in the Bias-Adjusted ECWMF Treatment was irrigated according to the CISSHY, provided in Table 1, when forecast probabilities were less than 60%.

The threshold for irrigation was set at 60% for the weather.com forecasts as well. If there was a 60% chance or more for precipitation during the Monday through Wednesday time period (Sunday forecast) or Thursday through Sunday time period (Wednesday forecast), then irrigation was not applied. Cotton included in the Weather.com Treatment was irrigated according to the CISSHY, provided in Table 1, when forecast probabilities were less than 60%.

Forecast verification. There are many different ways to verify and compare weather forecasts. One common method is by compiling a 2-X-2 contingency table (Nurmi, 2003). Contingency tables separate forecasts into four distinct categories as shown in Table 2: hits (a), false alarms (b), misses (c), and correct rejections (d). Although categorically different, the two forecasts used in this experiment were converted into simple binary (or yes/no) forecasts using a defined probability threshold.

Table 2. 2-X-2 Contingency Table. Contingency tables separate forecasts into four distinct categories (a-d). The variables generated from these categories are used to evaluate forecast performance

Event Forecast	Event Observed		Marginal Total
	Yes	No	
Yes	a[z]	b[y]	(a+b)[x]
No	c[w]	d[v]	(c+d)[u]
Marginal Total	(a+c)[t]	(b+d)[s]	n = (a+b+c+d)[r]

[z] referred to as a Hit.

[y] referred to as a False Alarm.

[x] total number of times the event was forecast.

[w] referred to as a Miss.

[v] referred to as a Correct Rejection.

[u] total number of times the event was not forecast.

[t] total number of times the event was observed.

[s] total number of time the event was not observed.

[r] total number of forecasts in the season.

Binary analysis. Bias-Adjusted ECMWF EPS forecasts were grouped into the "yes" category if the probability of exceeding one of the set threshold precipitation levels exceeded the probability limit (60%); otherwise, the forecasts were grouped into the "no" category. Weather.com forecasts were classified into the yes category if the probability limit was exceeded. Observations were included in the no category for the Bias-Adjusted ECWMF EPS forecasts when the forecasted precipitation threshold was not observed; likewise, forecasts were grouped into the yes category when the threshold was met or exceeded. Similarly for the weather.com forecasts, observations were included in the no category when the recommended amount of precipitation for the time period was not observed and were classified in the yes category when the recommended amount of precipitation for the time period was observed.

Categorical analysis. Several useful variables can be defined based upon combinations and ratios of the different categories contained in a contingency table. These variables are commonly used in the atmospheric sciences to verify and compare forecast performance. In particular, the Hit Rate (HR or Probability of Detection, POD, defined below in Eq. 3) and the False Alarm Ratio (FAR, defined below in Eq. 4) can be used together to evaluate forecast performance. Calculations of HR and FAR for this experiment are included in Table 3 (Nurmi, 2003).

Table 3. Hit Rate, False Alarm Ratio and Bias calculated for the Bias-Adjusted ECMWF EPS and weather.com forecasts. These calculations are used to judge forecast performance

Verification Variable	Bias-Adjusted ECMWF EPS	Weather.com
Hit Rate (HR)	0.2	0
False Alarm Ratio (FAR)	0.6	1
Bias (B)	0.5	1.2

$$HR = a / \left(a + c\right) \tag{3}$$

$$FAR = b / \left(a + b\right) \tag{4}$$

The HR measures the proportion of observed events that were correctly forecast, whereas the FAR measures the proportion of events incorrectly forecast. Values for HR range between 0 and 1, with 1 being a perfect score, whereas values for FAR vary between 0 and 1, with 0 being a perfect score.

The Bias (B) is also included in Table 3 and defined in Eq. 5. Although Bias is not an indicator of accuracy, it is useful in evaluating how a system behaves with respect to forecasting a given event (Nurmi, 2003). Bias values greater than 1 indicate the system over-predicts an event, bias values less than 1 indicate the system tends to under-predict, and bias values equal to 1 indicate the system is unbiased.

$$B = (a+b)/(a+c) \quad (5)$$

Statistical analysis. Statistical analysis was performed in MATLAB (R2014b) using two-way analysis of variance (ANOVA) followed by a multiple comparison of means.

RESULTS AND DISCUSSION

The objective of this experiment was to demonstrate the potential of using precipitation forecasts to schedule irrigation. The ECMWF EPS is introduced, with the option to use its forecast data to predict the probability of exceeding predetermined threshold values of precipitation. Bias adjustments and forecast data from the surrounding area are included in the analysis to de-emphasize any sub-grid scale anomalies (such as convective precipitation) occurring at one point that might not be representative of the entire area. It is contrasted with a more common forecast issued by The Weather Channel, which does not provide information pertaining to the amount of rainfall anticipated and is issued for a single location.

Forecast analysis. Table 3 lists the HR and FAR for the Bias-Adjusted ECWMF EPS forecasts and the weather.com forecasts. The Bias-Adjusted ECMWF EPS forecasts out-performed the weather.com forecasts with respect to HR and FAR, although there is room for improvement. It is also interesting to note that the weather.com forecasts did not correctly predict any rainfall events throughout the season, meaning that on the six times the forecast predicted rainfall (13 June, 11 July, 22 July, 25 July, 8 August, and 12 August), none of the events met or exceeded the recommended amount of water for irrigation. Therefore, a producer using these forecasts would have withheld irrigation during time periods in which rainfall either did not occur or the amount of observed was less than the amount recommended.

Q-to-q corrections were applied to the ECMWF EPS forecasts during the experiment in an effort to reduce bias; however, bias remained. Values for B found in Table 3 indicate that the Bias-Adjusted ECMWF EPS system tended to under-predict rainfall events, whereas the weather.com forecasts tended to over-predict precipitation. From a producer standpoint, it could be more beneficial to choose a forecast system that, to an extent, tends to under-predict rainfall rather than over-predict, thus protecting against water stress. If this were the case, the Bias-Adjusted ECMWF EPS forecasts would be a better choice both in terms of B and overall forecast performance.

Water applied. Total water applied for each treatment was calculated by summing all the irrigation applications during the season. Water applied over the course of the season totaled 34.80 cm, 31.93 cm, and 26.67cm for the Bias-Adjusted ECMWF, the Weather.com, and Check-book treatments, respectively. The larger amount of water applied to the Bias-Adjusted ECMWF Treatment reflects the tendency to under-predict rainfall indicated by the values for B calculated in the previous section. Similarly, the smaller amount of water applied to the Weather.com Treatment reflects the tendency for these forecasts to over-predict precipitation.

Yield. Yields from the Bias-Adjusted ECMWF Treatment were the greatest followed by the Weather.com Treatment, the Check-book Treatment, and the Rainfed Treatment, averaging 1796 kg/ha, 1717 kg/ha, 1692 kg/ha and 730 kg/ha, respectively. Because there was no interaction between irrigation method and cultivar, the statistical analyses for the two varieties were combined and are presented in Table 4. The results show that yields from the Rainfed Treatment are significantly different (lower) than the irrigated treatments. There is no significant difference among yields of the irrigated treatments (the Check-book Treatment, the Bias-Adjusted ECWMF Treatment, or the Weather.com Treatment) at a 95% confidence level.

Table 4. Statistical Analysis. Two-way analysis of variance (ANOVA) followed by a multiple comparison of means was performed as the statistical analysis. Because there was no interaction between irrigation method and cultivar, the statistical analyses for the two varieties were combined

Yield Comparison between Treatments		*p*-values[z]
Check-book Trtmt	Bias-Adjusted Trtmt	4.00E-01
Check-book Trtmt	Weather.com Trtmt	1.00
Check-book Trtmt	Rainfed Trtmt	0.00
Bias-Adjusted ECMWF Trtmt	Weather.com Trtmt	6.0E-01
Bias-Adjusted ECMWF Trtmt	Rainfed Trtmt	0.00
Weather.com Trtmt	Rainfed Trtmt	0.00

[z] *p*-values < 0.05 indicate statistically significant differences in mean yields.

The Check-book Treatment was included primarily as a yield comparison for the two forecast treatments. The results of this short study indicate that it might be possible to use precipitation forecasts to maintain yield at levels comparable to those one would expect using the check-book method. Therefore, instead of keeping record of past rainfall as with the check-book method, producers could save time by simply looking at the precipitation forecast to schedule irrigation.

FUTURE WORK

The creation of a forecast system designed to serve agricultural interests and provide information specifically tailored for the agricultural industry has the potential to make a large positive impact both within and beyond the irrigation sector. To accomplish this, however, work needs to be done to improve the accuracy of ECMWF EPS and weather.com forecasts in southern Georgia and other areas of intense agricultural industry. Work has begun to characterize the ECMWF EPS performance over the southern Georgia region. This work will be key in determining how to improve forecast accuracy. Once the forecasts have been optimized, it would be beneficial to run a series of field trials over a period of several seasons to further study the usefulness of precipitation forecasts with respect to scheduling irrigation.

Additionally, more research needs to be done on the manner and timing in which forecasts are used. There are many different methods producers use to irrigate. The only one explored in this research was the check-book method. Therefore, it would be constructive to use precipitation forecasts in conjunction with additional methods such as the use of sensor systems to see if results could be further optimized.

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